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Use of deep learning in leaf natural frequency analysis for plant water stress estimation

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1. Introduction

Optimal irrigation control is important not only for water conservation but also for keeping plants healthy and producing tasty crops. When plants are over- or under-irrigated, they are subjected to water stress, resulting in wilting of leaves and other symptoms. However, moderate water stress is considered desirable, and to achieve such a state, it is necessary to estimate plant water stress noninvasively and sensitively in real time based on the speaking plant approach (SPA).

Non-invasive estimation of water stress in plants has been studied from various angles, for example, spectroscopic methods such as leaf color, red edge, and infrared absorption by water[1-3] , leaf temperature measurement[4], observation of leaf projection[5] and photosynthesis (PSII) by chlorophyll fluorescence[6]. Then, we have been studying the possibility of detecting water stress in plants from changes in the natural frequencies of leaves as a new method[7, 8].

As a result, the natural frequency of one leaf, including the petiole, of a one-month-old komatsuna plant grown in soil with bottom water supply showed diurnal changes as shown in **Fig. 1**. A few days after the irrigation was stopped, the tendency was reversed, and the natural frequency during the daytime was found to be much lower than at night. Two days later, the leaves wilted. Thus, the state of water stress in the plant could be quickly estimated from the change in natural frequencies.

2. Method

2.1 Observation of natural frequency of leaf

Figure 2 shows the setup for measuring the damped vibration of a leaf. In this experiment, the leaves were pressed uniformly with acoustic radiation pressure from a 40 kHz ultrasonic source to produce damped vibrations, which were captured by a webcam on a PC.

However, since it is difficult to automatically select feature regions to be tracked by the correlation tracking method, we proposed a method to divide a frame image of a leaf into blocks and measure the frequency of variation of the mean value of each block[9]. That is, first, after extracting and binarizing leaves as shown in **Fig. 3** (a), the frame image is divided into blocks as shown in (b), and the average of the pixel values in each block is obtained. Next, the time variation is recorded for a 5×5 area within it. As a result, waveforms associated with leaf decay vibration are recorded in several blocks, as shown in (c).

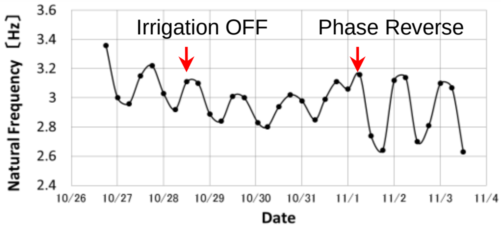


Fig. 1. Diurnal change of natural frequency of leaf.

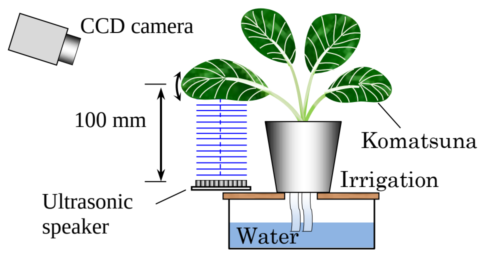
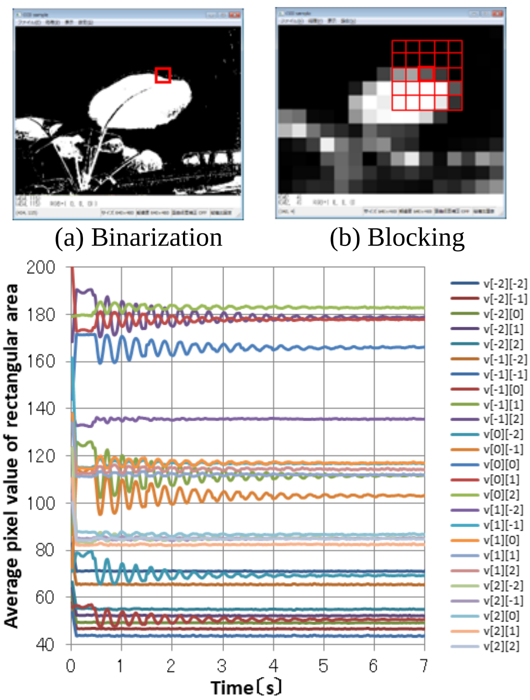


Fig. 2. The experimental setup



(a) Binarization (b) Blocking

(c) dumping curve of each block

Fig. 3. Block area and dumping curve

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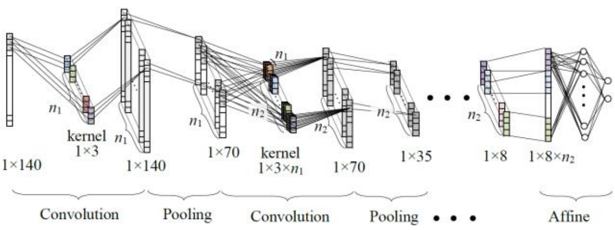
It is necessary to select an appropriate block from among these blocks and calculate its natural frequency, but a person must decide which block to adopt. We are considering the possibility of using deep learning for this decision.

2.2 Deep Learning

Deep learning is a type of machine learning that increases both the number of layers of a hierarchical neural network and the number of neurons in each layer to learn from huge amounts of data. Convolutional Neural Networks (CNNs) are known to significantly improve performance, especially for images. CNN is a method that extracts image features by convolution and pooling, and classifies them with a conventional hierarchical neural network (all connected layers).

In this study, 1D CNN was used by considering the time series data as 1D images. The input data (decaying waveform) is unified to 140 points, and convolution is first performed with n_1 (=8) types of 1×3 filters. Next, the data length was reduced to 70 points by max-pooling. Then, convolution is performed with n_2 (=8) types of $1\times3\times n_1$ filters, and max-pooling is used to further reduce the data length to half (35 points). These processes are repeated two more times to reduce the data length to 8. The $8\times n_2$ data are then rearranged into a single column and input to the all-connected (affine) layer. In the all-connected layer, the number of nodes in the intermediate layer is 16 and the number of nodes in the output layer is 2. The network structure is shown in **Fig. 4** (a) and the number of nodes in each layer is shown in (b).

As the development environment, we employed the Neural Network Console of Sony Network Communications Inc. which allows easy design of CNNs.



(a) Structure

Process	Node size
INPUT	1×140
Convolution×16 kernel(1×3)	16×1×140
ReLU	
MaxPooling(1×2)	16×1×70
Convolution×16 kernel(1×3×16)	16×1×70
ReLU	
MaxPooling (1×2)	16×1×35
Convolution×16 kernel(1×3×16)	16×1×35
ReLU	
MaxPooling(1×2)	16×1×17
Convolution×16 kernel(1×3×16)	16×1×17
ReLU	
MaxPooling(1×2)	16×1×8
Affine	16
ReLu	
Affine	2
Softmax	
CrossEntropy	1

(b) Size table

Fig. 4. Used neural network

The activation function was the general ReLU and the outputs were normalized to a total of 100 % with the SoftMax function. The optimization algorithm was Adagrad, the learning coefficient was 0.01, the number of training cycles was 100, and the loss function was the cross-entropy error.

4. Result

First, the 4,600 decay waveforms shown in **Fig. 3**(c) were classified into decay and other waveforms to create a dataset for training. Next, half of the dataset was used for training the neural network. Finally, the other half of the dataset was used to evaluate the decay curve judgment. As a result, the discrimination accuracy (correct response rate) was 98.17 %.

5. Conclusion

In this paper, for the purpose of optimal irrigation control, we focused on water stress in plants and examined the possibility of using deep learning to determine the changes in the natural frequency of leaf that appear because of the water stress. As a result, relatively good accuracy was obtained, although the number of data used for training and the design of the CNN are still insufficient.

In the future, we plan to improve the neural network by increasing the number of training data, as well as reexamining the activation function and optimization function, and changing the number of layers, aiming for further improvement in accuracy.

Acknowledgment

This work was supported by JSPS KAKENHI Grant Number 20K06328 and 21K05855.

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